Estimating Consumer Switching Costs in Chinese Mobile Communications Market

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1 Introduction

China is the largest market of mobile communications by subscriber in the world. As of June 2018, there are approximately 1.5 billion mobile phone subscriptions registered[1]. Since the nation-wide consolidation by the government in 2008, the mobile communications market has remained a 3-player oligopoly. China Mobile is the largest player with a market share of 62% by subscriber. China Telecom and China Unicom roughly split the rest of the market equally. The Chinese

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[1]Source: National Bureau of Statistics of China.

government plays an active role in the market, owning a controlling stake in each of these three companies. While it does not directly interfere with pricing decisions of the companies, it regulates the price level through policies and directives. For example, it abolished data and voice inter-provincial roaming charges in July and September 2017 respectively. In recent years, it also implemented policies to weaken the dominant position of China Mobile, by for example granting licenses for the much coveted low-frequency band to China Telecom and China Unicom in 2016 to facilitate their 4G expansion in rural areas. The market has also seen a few waves of price wars, often coinciding with technological migration from 2G to 3G, then from 3G to 4G.

Despite the government's attempts to promote competition and waves of price wars in the market, the Chinese consumers have shown remarkably strong loyalty towards their mobile carriers. According to a 2015 Deloitte market research report, 47% users surveyed never changed carriers[2]. While inertia in consumption pattern alone does not prove the existence of switching costs, certain regulatory and industrial features in the Chinese mobile telecommunications market, however, do suggest that consumers experience positive switching costs when they change carriers. First, consumers in most parts of China are not allowed to transfer their current mobile numbers to the new carriers when they switch (i.e. mobile number portability is not enforced nation wide). Second, due to incompatibility

[2]Source: 2015 Deloitte China Mobile Consumer Survey.

in network standards among the three carriers, certain handsets do not function or deliver lower Internet speed on competitors' networks.

Farrell and Klemperer (2007) give a comprehensive summary on the economic effect of switching costs. They posit that switching costs arise when a consumer must duplicate an investment specific to her current seller for a new seller. They may be learning, transactional or contractual costs. If firms can commit to future prices, then they compete on "lifecycle" prices in a Bertrand model. In this case, "the outcome is efficient and switching costs confer no market power on firms". However, if there are commitment problems, switching costs may or may not raise oligopoly profits depending on the specifics of the model. In the case where firms can distinguish old customers from new, switching costs allow them to price discriminate hence transfer rents from consumers to firms. While rational expectations of firms or consumers (or both) could reduce the size of the transfer through inducing greater ex ante competition, it "often fails to compete away ex post rents". As a result, switching costs raise oligopoly profits and hurt consumer surplus.

The theoretical literature on switching costs goes all the way back to Selten's (1965) model of "demand inertia". The model assumes that a firm's current sales partially depend on its sales in the past though it does not explicitly model switching costs (Farrell and Klemperer (2007)). The most significant contributor to the theoretical literature on switching costs is arguably Klemperer. Klemperer

(1987a) constructs a two-period duopoly model with homogeneous products and shows that switching costs can cause ex ante homogeneous products to become ex post heterogeneous. As a result, forward looking companies compete vigorously for market share in the first period and reap monopoly profits in the second. Using the same model, Klemperer (1987b) finds that switching costs make demand less elastic in both periods. While prices in the first period are lower than in the second, they may be higher in both periods than those without switching costs. Farrell and Shapiro (1988) maintain the assumption of a duopoly with homogeneous products but replace the two-period assumption with an overlapping generation setting to analyze the effect of switching costs on entry. They find that in equilibrium the incumbent typically specializes in serving the existing customers and concedes new ones to its rival. Entry may take place even when it is inefficient. Beggs and Klemperer (1992) further relax the assumptions to allow for infinite-period duopoly with spatial differentiation. With switching costs, they find that prices and profits are both higher. Switching costs also make market more attractive to a new entrant.

There is also a large body of empirical literature on switching costs both from economics and marketing fields. Farrell and Klemperer (2007) provide a comprehensive list of economics empirical studies and Seetharaman et al. (1999) summarize the marketing literature. Where micro data on individual consumers' purchases are available, it is standard to use a discrete choice approach to explore the determinants of a consumer's probability of purchasing from a particular firm. Two key issues must be addressed when attempting to estimate switching costs. First, unobserved heterogeneity must be controlled for. As Heckman (1981) points out, observed persistence in consumer brand choice can be caused by heterogeneity ("spurious state dependence") or state dependence ("structural state dependence"). The latter includes searching, switching and learning costs. Without properly controlling for heterogeneity, including unobserved heterogeneity, inertia is entirely attributed to switching costs, subsequently leading to overestimation. Keane (1997) compiles a list of seven types of heterogeneity, out of which five are unobserved. Second, informational friction, which manifests through inattention or incomplete consideration set, confounds with switching costs and if uncontrolled for, also causes overestimation of switching costs. Shum (2004) does not control for inattention or incomplete consideration set and finds an average switching costs of cereal as high as $3.43, more than the price of a typical box of cereal. Ho et al's (2017) paper on Medicare Part D assumes away switching costs and solely models inattention. Only when information on consumer's informational friction is available, it is possible to separately identify switching costs. Honka (2014) has access to survey data that indicate consumers' consideration sets when choosing auto insurance. Handel and Kolstad (2015) conduct a survey to tease out state dependence caused by inaccurate information from switching costs.

While the effect of switching costs on firm profitability varies from model to model, economic theory generally predicts a welfare reduction for consumers when switching costs are present. It is therefore both an interesting and an important economic question to quantify this welfare loss. In this paper, I use a novel data set provided by one of the Chinese mobile carriers and supplement it with market information and simulated data to construct a random sample of the postpaid users in a large Chinese city for a 11-month period and estimate the switching costs of the individuals in this sample using a discrete choice model. The preliminary estimation results suggest monthly switching costs between RMB564 (US$82) and RMB705 (US$103). This range appears high considering the mean monthly price in the carrier's data is RMB79 (US$12). High reconsideration frequency, model mis-specification and not controlling for unobserved heterogeneity could all contribute to these high estimates. In the next steps of the project, I will address each of these issues.

The remainder of the paper is organized as follows: Section 2 describes the data; Section 3 introduces the theoretical model; Section 4 discusses the empirical strategy and estimation methodology; Section 5 presents the preliminary estimation results; Section 6 concludes and outlines the next steps.

2 Data Description

The original data are provided by one of the Chinese carriers ("Carrier A"). It contains monthly subscription information for all Carrier A's users in a large city in China ("City B") from November 2016 to October 2017. I observe, for each user, a unique user ID, the name of the plan she subscribed to in a particular month, as well as the gender and age group of the user. The original data set includes 3.9 million unique users and 33.7 million observations of plan names[3]. There are in total 615 unique plan names, of which the top 200 account for over 99% of all observations. I collect the attributes of these 200 plans from various Internet sources[4]. As the focus of this paper is on postpaid consumers, I exclude plans that have no monthly charge and/or use an online charging system as these plans have a strong prepaid nature. Typically, a user with such a plan tops up the account by her selected amount of credit at any frequency. The credit is then deducted in real time as the user makes calls, sends text messages or browses the Internet. In addition, I also exclude plans that are not sold to retail customers, such as plans for employees of particular companies or government agencies. After

[3]These numbers are only for users with demographic information. If users without demographic information are included, there are 4.4 million unique users and 37.5 million observations of plan names in the original data set.

[4]Main sources include Carrier A's website, Baidu Baike (the Chinese equivalent of Wikipedia), Baidu Zhidao (the Chinese equivalent of Quora).

the selection process, 65 plans remain, which account for 2.5 million unique users and 19.7 million observations.

Switching information is inferred from comparing the lists of unique user ID's from two consecutive periods. If a user ID is seen in the list from period t-1 but not in that from period t, this user is assumed to have switched out in period t. Similarly, a user is treated as having switched in during period t if her unique user ID is in the period t list but not in the period t-1 list. In the data set, there are about 11% of users who switched more than once, and 1% of users who switched more than twice. While it is possible that some users switched more frequently than others, it is nevertheless unlikely that such a high proportion of users did so. Possible explanations include data entry error and missing information. Since the exact reason behind this unusual switching pattern is not clear, I exclude the observations related to these users from the data set. Observations from the first period (November 2016) are also dropped since switching information for this period is not available. After the data cleaning process, there remain 2.1 million unique users and 17.2 million observations in the data set.

3 Model

3.1 Main model assumptions

Before introducing the model, I first discuss the main assumptions on consumers' decision making process. At the beginning of each month with probability σ, a consumer is to reconsider her choice of mobile communication services in a two-stage process: (i) choose a mobile carrier between Carrier A and "Rival", which is an aggregated carrier of the other two Chinese carriers (there is no outside option); (ii) select a particular plan from the chosen carrier in step (i). With probability $1-\sigma$, the consumer does not reconsider her choice and stays with her carrier from the last period and rolls forward the same plan. With the two-stage assumption, I focus my attention on modelling the decision making process of the first stage, which is directly relevant to switching costs. Aggregating the remaining two carriers, and assuming away the outside option simplifies the modelling process. Given the mobile penetration rate, defined as the number of mobile subscriptions divided by the population, is over 100%[5] in China and City B's GDP per capita in 2016 is above the national average [6], it is reasonable to assume that in reality the outside option of not having any mobile communications services is not a

[5]Source: National Bureau of Statistics of China.

[6]China's GDP per capita in 2016 is RMB53,974 (source: National Bureau of Statistics of China)

viable choice for consumers in City B. This assumption would need to be revised if I later carry out counterfactual analyses in which both carriers significantly increase prices. As long as prices are below a reasonable level, this assumption should be justifiable.

3.2 Utility function

Formally, consumer i's indirect utility for choosing carrier j in period t is given by

$$u_{ijt} = v_{ijt} - \beta_i I_{i,j,t-1} + \epsilon_{ijt} \tag{1a}$$

where

$$v_{ijt} = \alpha_{ij} + \gamma E[p_{ijt}] + E[W'_{ijt}]\phi_j \tag{1b}$$

$$\beta_i = \tilde{\beta} + Z'_i \tau \tag{1c}$$

The utility function comprises three parts: v_{ijt}, the expected utility of individual i from subscribing to and consuming services offered by carrier j; $\beta_i I_{i,j,t-1}$, the potential switching costs incurred by i when choosing j; and ϵ_{ijt}, an idiosyncratic shock, which is assumed to follow an i.i.d. Type 1 extreme value distribution.

α_{ij} measures carrier-specific unobserved heterogeneity across individuals. I assume (α_1, α_2) follows a binormal distribution. At the first stage of decision making, the consumer is assumed to be unaware of the plans offered by either Carrier A or Rival, other than the one she used in the last period. As a result, she evaluates her carrier choice using the expected price $E[p_{ijt}]$ and expected plan attributes $E[W_{ijt}]$. Plan attributes include allowance for voice call and data, as well as an indicator which shows if the plan allows for unlimited data usage for certain services (e.g. Wechat). Since a consumer's plan choice reflects her living environment and underlying preference (for example a heavy video streamer without easy access to WiFi would select a plan with large data allowance) and if we assume these two elements do not change often, a consumer would likely expect to select a plan very similar to the one she used in the last period in terms of attributes at the second stage regardless which carrier she chose at the first stage. By this reasoning, I assume $E[W_{i1t}] = E[W_{i2t}] = W_{ik,t-1}$, where $k = 1, 2$ is the carrier consumer i was with in t-1. The price expectations are formed in a similar way. Her expected price for staying with the her t-1 carrier is equal to the actual price she paid in t-1, i.e. $E[p_{ikt}] = p_{ik,t-1}$. Her expected price for switching to the other carrier can be written as $E[p_{i,-k,t}] = \delta_{it} \cdot p_{ik,t-1}$, where δ_{it} is consumer i's expected price ratio between the two carriers for her current plan in t. δ_{it} is assumed to be formed with negligible search costs, for example from conversations with friends and family and/or from advertising campaigns.

The parameter γ captures consumers' price sensitivity and is expected to have a negative sign. ϕ_j is a vector that measures the marginal utility of each plan attribute. It is carrier specific. The difference between ϕ_1 and ϕ_2 is attributed to difference in actual or perceived quality. For example, if the network speed of Carrier A is faster than that of Rival, then the marginal utility of one more unit of data from Carrier A is likely higher than that from Rival.

$I_{i,j,t-1}$ is a dummy variable which indicates if switching costs are incurred. It takes the value of 1 if consumer i's carrier last period is not j and takes the value of 0 if consumer i's carrier last period is j. The switching costs β_i includes a constant $\tilde{\beta}$ and a second part that varies with Z_i, a vector of demographic factors. I assume switching costs are not carrier specific. In other words, for the same individual i, her switching costs from Carrier A to Rival in period t are the same as her switching costs from Rival to Carrier A.

4 Empirical Strategy

4.1 Empirical model

Since there are two carriers in the market, let j=1 denote Carrier A and j=2 denote Rival. As in all discrete choice models, the level of utility is not identified. I therefore normalize v_{i2t}, the expected utility from subscribing and consuming services from Rival, to zero. u_{ijt} becomes

$$
\begin{aligned}
u_{i1t} &= v_{i1t} - v_{i2t} - \beta_i I_{i,1,t-1} + \epsilon_{i1t} \\
&= (\alpha_{i1} - \alpha_{i2}) + \gamma(E[p_{i1t}] - E[p_{i2t}]) + (E[W_{i1t}]'\phi_1 - E[W_{i2t}]'\phi_2) - \beta_i I_{i,1,t-1} + \epsilon_{i1t} \\
&= (\alpha_{i1} - \alpha_{i2}) + \gamma(E[p_{i1t}] - E[p_{i2t}]) + W'_{ik,t-1}(\phi_1 - \phi_2) - \beta_i I_{i,1,t-1} + \epsilon_{i1t} \\
&= \hat{\alpha}_i + \gamma(E[p_{i1t}] - E[p_{i2t}]) + W'_{ik,t-1}\hat{\phi} - \beta_i I_{i,1,t-1} + \epsilon_{i1t} \qquad (2a)
\end{aligned}
$$

$$
u_{i2t} = -\beta_i I_{i,2,t-1} + \epsilon_{i2t} \qquad (2b)
$$

$\hat{\alpha}_i$ is the difference between two normally distributed random variables hence also follows a normal distribution. Its mean, $\bar{\alpha}$, and variance, σ_α^2, can be identified using simulation. However, the mean and covariance matrix of the binormally distributed (α_1, α_2) are not identified.

Ass in the data set, the only prices I observe are Carrier A's prices. I therefore assume that consumer i's expected price for Carrier A is equal to the actual period t price she pays if she is a Carrier A user in period t, i.e. $E[p_{i1t}] = p_{i1t}$. If she switches from Carrier A to Rival in t, then I assume her expected price for Carrier A is equal to the actual period t-1 price, i.e. $E[p_{i1t}] = p_{i1,t-1}$. Since there is no information on Rival prices, I simply assume $E[p_{i2t}] = \delta \cdot E[p_{i1t}]$ for all i and all t. I then make use of the average revenue per user ("ARPU") figure reported by each carrier on a quarterly basis to benchmark for δ. Based on the average of the 11-month period, δ is approximately 1.2.

Similar to the case of $\hat{\alpha}_i$, ϕ_1 and ϕ_2 cannot be separately identified. Their difference, $\hat{\phi}$, which measures the difference in marginal utility between Carrier A and Rival, can be identified. Note that elements of vector $\hat{\phi}$ can take either positive or negative signs.

There are in total four sets of parameters to be estimated: parameters related to the distribution of $\hat{\alpha}_i$ ($\bar{\alpha}$ and σ_{α}^2), marginal utility difference $\hat{\phi}$, and the two key parameters, price sensitivity γ and switching costs β_i ($\tilde{\beta}$ and τ). γ is expected to be negative and β_i positive. $-\frac{\beta_i}{\gamma}$ gives the switching costs in monetary terms.

4.2 Simulated maximum likelihood estimation

In an ideal world where complete market data are available, the most appropriate estimation methodology for this model would be simulated maximum likelihood estimation (SMLE). Using the logit formula, the probability of consumer i choosing carrier j in period t conditional on reconsideration is:

$$P_{ijt} = \frac{exp(v_{ijt} - \beta_i I_{i,j,t-1})}{exp(v_{ijt} - \beta_i I_{i,j,t-1}) + exp(v_{i,-j,t} - \beta_i I_{i,-j,t-1})} \tag{3}$$

Consider consumer i, whose carrier in t-1 is Carrier A, i.e. $s_{t-1} = 1$. The unconditional probabilities for i to choose Carrier A (j=1) and Rival (j=2) in t are

$$\mathbb{P}_{i1t} = \sigma P_{i1t} + (1 - \sigma) \tag{4a}$$

$$\mathbb{P}_{i2t} = \sigma P_{i2t} \tag{4b}$$

Note that the crucial difference between the two unconditional probabilities is that consumer i could either "actively" choose Carrier A, her carrier in t-1, by reconsidering her choice and making the decision to stay (σP_{i1t}), or "passively" choose Carrier A by not reconsidering her choice and letting her subscription roll forward ($1-\sigma$). However, she could only "actively" choose Rival. In other words, when switching is observed, the consumer must have reconsidered her choice.

The overall log likelihood function is

$$\mathcal{P} = \sum_{i,t} log(\mathbb{P}_{ijt}) \tag{5}$$

4.3 Missing information

With only data from one carrier, SMLE is not an appropriate methodology. As illustrated in Figure 1, there are four different groups of consumers in the market from period t-1 to t. There are consumers who subscribe to the same carriers in t-1 and t, represented by the two ovals labelled "Carrier A" and "Rival". There are also consumers who switch from Carrier A to Rival ("Switch-out") and those who switch from Rival to Carrier A ("Switch-in") at the beginning of t. In the data, I only observe three out of these four groups: "Carrier A", "Switch-out" and "Switch-in". Information of the "Rival" group is the missing. In general, if information is missing at random, the estimates from SMLE are unbiased. However, in this case, the Rival group likely consists of individuals who, compared to the population average, prefers Rival to Carrier A, are less price sensitive and most important, have higher switching costs. Omitting the Rival group will lead to biased estimation in all parameters.

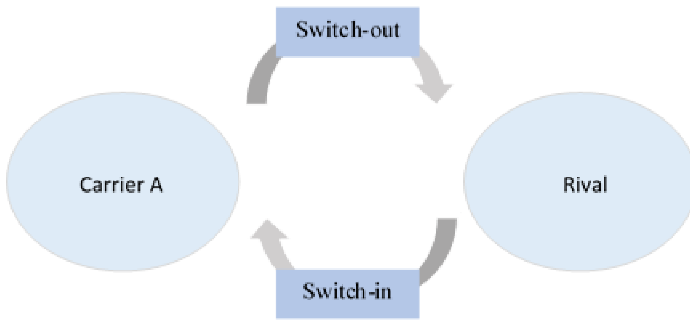

Figure 1: Consumer movement in the mobile communications market

To deal with this problem, there are two possible solutions. The first is to supplement the existing data with additional market information on Rival's users. For example, a user survey on plan attributes and demographic information and how long the user has been with the carrier would provide sufficient information on key characteristics. By using the data on the Switch-in group, distributional pattern of plan attributes and demography on the Rival group can be teased out. It is then possible to simulate data for the Rival group with reasonable accuracy. However, survey data are often costly and it takes time to obtain them. The second solution is to use General Methods of Moments (GMM) instead of SMLE. With appropriately selected population moments, it could be possible to correct for the bias caused by the missing information. While this solution is methodologically more sound, it nevertheless requires a lot more consideration therefore is difficult to complete within the time frame of this paper. In this paper, I will employ a methodology in the same spirit as the first solution by using the distributional pattern in the actual data and making some necessary, albeit strong, additional assumptions to obtain preliminary estimates of the switching costs.

4.4 Estimation using hybrid data

I first simulate data for the Rival group to supplement the actual data. To facilitate simulation, I simplify the model by letting $\hat{\alpha}_i$ equal to a constant $\tilde{\alpha}$. In other words, I no longer control for unobserved heterogeneity. The utility functions become

$$u_{i1t} = \tilde{\alpha} + \gamma(E[p_{i1t}] - E[p_{i2t}]) + W'_{ik,t-1}\hat{\phi} - \beta_i I_{i,1,t-1} + \epsilon_{i1t} \tag{6a}$$

$$u_{i2t} = -\beta_i I_{i,2,t-1} + \epsilon_{i2t} \tag{6b}$$

This simplification is done out of necessity. With unobserved heterogeneity, simulations must be done at unique user level. In other words, I have to simulate the decisions made by each individual who is a Rival user in any period for all subsequent periods until she switches out. Further, I must make sure each period those who switch out from Rival in the simulated data match with those who switch into Carrier A as observed in the actual data. This requirement renders simulation infeasible. Without unobserved heterogeneity, each individual can be completely described by her gender, age and attributes of the chose plan. Consequently, one user making decisions in two periods is empirically equivalent to two users (with the identical gender, age and plan) making decisions in one period. As a result, I can remove the time dimension and conduct simulation at observation level rather than at unique user level. To obtain the total number of observations in the Rival group, I first pin down the number of Rival's unique users in the first period (November 2016) by multiplying the number of Carrier A's unique users by the ratio of the total national subscribers reported by the three companies. The assumption here is that the split of market between Carrier A and Rival in City B is not significantly different from that in the national market. As the scope of this paper is limited to postpaid subscribers, another implicit assumption of using the ratio of total subscribers is that for each carrier, the mix between postpaid and prepaid customers is the same in City B. The implied total number of postpaid subscribers in City B in November 2016 from this exercise is 6.6 million. To check if this number is sensible, I first estimate the total subscribers in City B by multiplying the city's population by the national mobile penetration rate, which comes up to approximately 11.5 million. The ratio between the numbers of postpaid and total subscribers gives a postpaid share of 58%. I did not find reliable information on the postpaid-prepaid split in China.

Typically in developing countries the postpaid share is below 50%. Given City B is economically more developed with a large urban population compared to the national average, the 58% number does not appear unreasonable. After pinning down the initial condition, I assume that the market is closed for the 11-month period, that is, there are no users entering or exiting the market. Using the initial condition and switching information observed in the actual data, I can work out how many users choose to stay with Rival each period. Summing up the numbers for the 11 periods, I arrive at a total number of observations in the Rival group of 57 million. I assume these observations follow the same distributional pattern in terms of demography and plan share as in the actual data. To avoid dealing with a large sample size, I simulate a sample of 1% the size of the Rival group, and combine it with a 1% random sample drawn from the actual data. Combining the two roughly gives 1% of the population in the two-carrier market described by the model. In the rest of the paper, I refer to this set of data as the "hybrid data".

Next, I carry out estimation by maximizing the overall log likelihood function given by equation (5). For simplicity, I set the reconsideration parameter σ to 1. The estimation results are reported in Section 6.2.

5 Preliminary Estimation Results

5.1 Monte Carlo simulations

I conduct four sets of Monte Carlo simulations to look for any potential identification issue with the empirical model.

For the first set, I use arbitrary parameters values. Each simulation contains 500,000 observations, of which 100,000 are initially assigned to Carrier A and the rest to Rival. I then randomly assign demographic information based on the distributional pattern in the actual data. For example in the actual data, the percentage of observations that are male is 65.8%. For each observation, I make a random draw from a standard uniform distribution. If the draw is smaller that or equal to 0.658, the observation is male; otherwise the observation is female. For price and plan attributes, I make random draws from the standard normal distribution for price, voice and data then take the absolute value, and from the uniform distribution for the indicator for unlimited data services, with any draw bigger than 0.5 taking the value 1 and 0 otherwise. Next I draw ϵ's from the Type 1 extreme value distribution and calculate u_{1i} and u_{2i} respectively for each observation. The simulation is repeated 10 times and the mean results are reported in Table 1, Set 1. The estimates are accurate with small deviation from the true parameter values and precise with small standard errors. This shows that with sufficient variation in plan attributes, all the parameters can be well identified.

The second set of simulation is identical to the first except instead of drawing price and plan attributes from random distributions, I assign the 65 plans in the actual data to the observations and make sure the share split among the plans matches that in the actual data. Estimation results are reported in Table 1, Set 2. All parameters remain accurate and precise except for the coefficient for price. The price coefficient is estimated with large inaccuracy and high standard error, which renders the estimate not significant at 10% level. This is likely caused by multicollinearity between price and plan attributes.

Next, I repeat the first two sets of simulations with a different set of parameter values. Instead of arbitrary values, I use the estimation results based on the hybrid data (see the next subsection) and report the results in Table 1, Set 3 and Set 4. The only difference between Set 1 and Set 3 is the parameter values used. The same applies to Set 2 and Set 4. In Set 3, the standard errors remain small. The accuracy of the estimation, however, varies from parameter to parameter. Those with small values tend to have less accurate estimates. In Set 4, the standard error for the price coefficient remains large. However, the ratio between the estimate and the standard error is higher and the estimate now is significant at 10% level. For those variables with small coefficients, rescaling could potentially improve estimation accuracy.

The Monte Carlo results show that while the price coefficient is estimated with some inaccuracy, it is within an acceptable range. The standard error of the price coefficient relative to the estimated parameter value is reduced when running the Monte Carlo using the estimated results rather than arbitrary values.

5.2 Preliminary estimation results

The estimation results using the hybrid data are reported in the first two columns of Table 2. All parameters are significant at 10% level. Both of the key parameters, the price sensitivity γ and switching costs β_i, have the expected signs. Based on the estimates, the implied switching costs in monetary terms calculated by $\frac{1000\beta_i}{\gamma}$ (multiplying by 1000 since prices are in RMB'000) are between RMB564 (US$82) and RMB705 (US$103) per month. Men incur lower switching costs than women. The age group that experiences the highest switching costs is those between 50 and 59.

These estimates appear high considering the mean monthly price in the actual data is RMB79 (US$12). There are a number of reasons that can account for this. First, the consideration parameter σ is assumed to be 1, that is all individuals reconsider their mobile services every month. In fact, given the subscription nature of the service, the actual fraction is likely to be significantly below 1. The consideration parameter confounds with the switching costs parameter and a high value of σ leads to an overestimation of the switching costs. The estimation results for σ equal to 0.5 can be found in the last two columns of Table 2. The estimated switching costs decrease to between RMB448 (US\$65) and RMB586 (US\$86). As a next step of the project, I will relax assumptions on σ and include it as a parameter to be identified using the model.

Another possible explanation is that by simplifying the three-player market to a two-player market, the users that switch between the two carriers (which are aggregated to form Rival) are "mis-classified" as non-switchers that choose to stay with Rival. Since switching costs are likely higher for non-switchers than switchers, this model simplification may have caused upward bias in switching costs estimates. Once I collect more data on the two carriers, I can modify the model to reflect a three-player market and potentially correct for this upward bias.

As discussed before, when unobserved heterogeneity is not controlled, switching costs are over estimated. However, the need for simulated data prevents me from controlling for it. Without individual level data from the two rival carriers, MLE is not appropriate without simulation. The only solution is to use GMM and make use of moment conditions at population level instead of MLE.

6 Conclusion and Next Steps

This paper is a first step in attempting to estimate switching costs of postpaid mobile subscribers in China. While the estimates appear to be biased upwards, I have identified a list of reasons that could account for the bias and will continue to work on addressing each of them.

As an immediate next step of the project, I will parameterize σ and investigate if σ can be identified. Identification of σ is achieved by sufficiently large variation in prices, which may or may not be available in the data. Next, I will collect more public information on prices and plan attributes offered by the two rival carriers to relax the assumptions I am currently rely on in this paper. With more granular information on these two carriers, the model can be re-written into a three-carrier market to correct for the bias introduced by over simplification. Last and most important, instead of using MLE, I will identify useful population moments for estimation using GMM. If there are enough population moments, there is a possibility that I do not need to rely on simulated data. Without the need for simulation, I can revert to the original specification of the model, in which unobserved heterogeneity is controlled for.

Table 1: Monte Carlo simulation results

	True param	Set 1 Est	Set 1 SE	Set 1 %Diff	Set 2 Est	Set 2 SE	Set 2 %Diff
Alpha (constant)	-1.0	-1.00	0.01	-0.4%	-1.00	0.01	0.0%
Gamma (price)	**-1.0**	**-0.99**	**0.04**	**-0.7%**	**-1.12**	**0.67**	**12.2%**
Voice	-1.0	-1.01	0.01	0.5%	-1.00	0.01	-0.2%
Data	1.0	1.00	0.01	0.2%	1.00	0.01	-0.1%
Unlimdata	-1.0	-1.00	0.01	0.4%	-1.00	0.02	0.3%
Swtch. costs (base grp*)	1.0	1.00	0.02	0.4%	0.99	0.02	-0.8%
Male	-0.5	-0.49	0.01	-1.4%	-0.49	0.01	-2.3%
Age: 20-29	1.0	0.99	0.02	-1.2%	1.00	0.02	0.2%
Age: 30-39	1.5	1.49	0.02	-0.4%	1.50	0.02	0.0%
Age: 40-49	2.0	1.99	0.02	-0.5%	1.99	0.02	-0.5%
Age: 50-49	2.5	2.49	0.03	-0.4%	2.50	0.03	-0.2%
Age: 60 & above	3.0	3.00	0.03	0.0%	3.01	0.03	0.4%

	True param	Set 3 Est	Set 3 SE	Set 3 %Diff	Set 4 Est	Set 4 SE	Set 4 %Diff
Alpha (constant)	-0.89	-0.89	0.02	-0.3%	-0.89	0.03	-0.4%
Gamma (price)	**-6.25**	**-6.25**	**0.04**	**0.0%**	**-6.31**	**1.23**	**1.0%**
Voice	0.14	0.14	0.01	-2.3%	0.14	0.02	0.3%
Data	-0.02	-0.02	0.01	-8.6%	-0.02	0.00	-6.8%
Unlimdata	2.02	2.02	0.02	-0.2%	2.01	0.03	-0.6%
Swtch. costs (base grp*)	3.57	3.57	0.03	-0.1%	3.58	0.04	0.3%
Male	-0.05	-0.04	0.01	-16.0%	-0.05	0.02	4.7%
Age: 20-29	0.30	0.30	0.02	-1.3%	0.29	0.04	-5.4%
Age: 30-39	0.58	0.58	0.02	-0.4%	0.57	0.04	-1.7%
Age: 40-49	0.75	0.74	0.02	-1.8%	0.73	0.04	-3.0%
Age: 50-49	0.83	0.82	0.03	-1.4%	0.79	0.05	-4.8%
Age: 60 & above	0.66	0.67	0.03	1.0%	0.68	0.05	3.1%

Notes:

1. Results shown are the mean of 10 simulations, each with 500,000 observations
2. Set 1 and 3 use price and plan attributes (voice, data, unlimited data indicator) drawn from random distributions
3. Set 2 and 4 use price and plan attributes from the actual data, assigned to observations based on the plan share in actual dataset
4. Base group for switching costs is female below 20

Table 2: Preliminary estimation results using hybrid data*

	Sigma = 1		Sigma = 0.5	
	Est	SE	Est	SE
Alpha (constant)	-0.89	0.02	-0.90	0.02
Gamma (price)	**-6.25**	**1.03**	**-6.30**	**1.06**
Voice	0.14	0.02	0.15	0.02
Data	-0.02	0.00	-0.02	0.00
Unlimdata	2.02	0.03	2.06	0.03
Swtch. costs (base grp*)	**3.57**	**0.03**	**2.87**	**0.03**
Male	-0.05	0.02	-0.05	0.02
Age: 20-29	0.30	0.03	0.29	0.04
Age: 30-39	0.58	0.04	0.57	0.04
Age: 40-49	0.75	0.04	0.75	0.04
Age: 50-59	0.83	0.04	0.83	0.05
Age: 60 & above	0.66	0.05	0.65	0.05

Notes:

1. Hybrid data consist of the simulated data for 1% of the Rival group and a 1% random sample from the actual data
2. The base group for switching costs is female below 20

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